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Forecasting UAE Electricity Consumption by Sector Using the NDGM Model, Based on Data from 2012 to 2021

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ABSTRACT

This work advances the efficiency of electricity demand forecasting in the United Arab Emirates (UAE) by utilizing the Non-Homogeneous Discrete Grey Model (NDGM) to predict electricity consumption from 2022 to 2040, with a focus on analyzing different sectors, filling up research gaps in this area. Based on historical data from 2012 to 2021, our model achieves a Mean Absolute Percentage Error (MAPE) of approximately 0.15%, indicating high accuracy. This makes our results more useful for energy planners and policymakers who want to make sure that supply matches demand and avoid overinvestment or load shedding. We also examine electricity use from a sector-specific perspective; a viewpoint that hasn't been explored in previous research. Furthermore, our analysis uses data from sources that are specific to the UAE, like the Department of Energy in Abu Dhabi, DEWA, SEWA, and FEWA. The analysis includes sector-wise consumption for 2021, Relative Growth Rate (RGR), and Doubling Time (Dt) metrics. Results show future steady demand growth, with commercial and residential sectors dominating. These insights support sustainable energy planning and highlight the need for efficiency measures in high-consumption sectors. We offer some recommendations specific to the UAE that explain our empirical results and help policymakers of the country in making appropriate decisions about the future desired electricity supply.

Keywords: Non-Homogeneous Discrete Grey Modelling, Forecasting Electricity Consumption, UAE
JEL Classifications: C22, Q41, Q47

1. INTRODUCTION

The UAE's electricity consumption has surged over the past decade, driven mainly by urbanization, industrial expansion, and extreme climatic conditions during summer months. Reliable forecasting models are essential to align supply with demand, mitigate energy shortages, and support the efforts the country is undertaking in developing renewable energy transitions. Therefore, accurate electricity consumption forecasting is critical for the UAE. Inaccurate forecasts can lead to overinvestment in generation capacity or load shedding, impacting economic and environmental sustainability.

The UAE has one of the utmost advanced and diversified economies in the Middle East. Initially, the country was reliant on oil and gas, but it has successfully expanded into tourism, finance, real estate, trade, and renewable energy. Key economic indicators (2024 forecast) show GDP (Nominal) of $500 billion, GDP per capita of $50,000, and economic growth rate of 4-5%, inflation rate: 3-4%, and unemployment rate of 3%. Main challenges facing the economy include dependence on the expatriate workforce (~90% of the private sector), geopolitical risks (regional tensions, oil price volatility), climate change and water scarcity and Competition from Saudi Arabia (Neom, Riyadh as a financial rival). The country has rapidly expanded its power generation capacity to meet growing demand driven by urbanization, industrialization, and economic diversification. As of (2023-2024, Total Installed Capacity was 45 GW, Electricity Generation was 150 TWh annually, Per Capita Consumption was 11,000 kWh (one of the highest globally) and electrification rate

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of 100%. The UAE relies on a combination of conventional and renewable energy sources, with natural gas contributing 80% of total electricity and nuclear power is expected to supply 25% of the UAE's electricity by 2025.

The remainder of this paper is structured as follows. Section 2 presents a survey of the existing literature on the subject matter. Section 3 discusses the dataset and the econometric methodologies. Section 4 presents and discusses the empirical results and lastly, Section 5 concludes the paper and makes some policy recommendations.

2. SURVEY OF LITERATURE OF ELECTRICITY FORECASTING MODELS

Previous studies have used various forecasting models for electricity demand forecasting, including ARIMA/SARIMA, regression models, exponential smoothing techniques, machine learning approaches, support vector machines (SVM), and grey models. These models have limitations such as linear assumptions, large data requirements, and difficulty adapting to structural changes. Recent studies have proposed alternative analysis based on growth rate decomposition to identify key determinants of electricity demand, enabling better planning for electricity production and transmission systems. The study also highlighted the importance of electricity efficiency improvements and price reform in managing future electricity demand effectively. The Gulf Cooperation Council (GCC) region used Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Linear Regression (MLR) models for forecasting long-term peak electricity demand, with the Neuro-Fuzzy model showing superior accuracy (AL-Hamada et al., 2019). The review identifies current trends and common practices in electricity demand forecasting in these regions, highlighting potential research gaps and recommendations for future studies to enhance forecasting accuracy and support informed decision-making for business entities and policymakers.

Chen et al. (2021) developed a seasonal grey prediction model, AWBO-DGGM (1, 1), to predict electricity consumption and usage efficiency in industrial sectors. The model achieved low MPEs in both training and testing, indicating that industrial electricity consumption, added value, and usage efficiency are expected to continue growing with seasonal fluctuations. Shah et al. (2022) proposed a two-component modeling approach for forecasting electricity demand and prices, focusing on multivariate modeling for enhanced performance. Ali Al-Ebrahim et al. (2024) improved electricity demand forecasting for GCC states using data mining and machine learning techniques. The Autoregressive Integrated Moving Average (ARIMA) method was found to provide the best forecasting performance, leading to improved resource optimization for generation expansion projects. Verma (2024) used Non-Homogeneous Discrete Grey Modeling (NDGM) to predict long-term electricity demand in the UAE, enabling informed decision-making for sustainable power sector management. Abosedra et al. (2024) used the autoregressive distributed lag model (ARDL) to explain the drivers of electricity demand in the UAE, finding that income, temperature, and population positively influence demand in the long run, while electricity prices appear to be negatively related to demand (Garcia et al., 2016).

He et al. (2017) proposed a method to handle uncertainty in short term electrical load forecasting by combining kernel-based support vector quantile regression (KSVQR) with Copula theory. It tests different kernel functions to find the best one, evaluates results using prediction interval metrics (PICP and PINAW), and captures dependencies (e.g. between load and price). Real data from Singapore show that with the right kernel the method produces accurate forecasts. Kumar et al. (2018) addressed the challenge of forecasting highly volatile electricity prices in deregulated markets, where prices play a key role in market evaluation. To improve forecasting accuracy, they proposed a hybrid model combining wavelet transform, SARIMA, and GJR-GARCH. The model separates price components for better prediction and is tested on data from the New South Wales electricity market, showing promising results. Goswami and Kandali (2020) forecasted electrical load in Assam using ARIMA and SARIMA models based on daily hourly data from SLDC, Kahilipara. By splitting data into training and testing sets, the models are evaluated using error metrics. Results show that SARIMA, which accounts for seasonality, outperforms ARIMA with lower prediction errors, making it more effective for load forecasting.

Lisi, F. and Shah, I. (2020) evaluated several models for 1-day-ahead forecasting of electricity demand and prices across four major markets. They use a two-step approach: nonparametric estimation of deterministic components, followed by modeling of stochastic residuals using various univariate, multivariate, and functional models. Among these, the double functional model consistently delivers the best or equally strong performance, demonstrating the effectiveness of the functional approach over a full year of predictions. Alsulaili et al. (2024) explore how weather conditions affect electricity use in arid regions by applying statistical (MLR, MTS) and machine learning (XGBoost) models. All models showed high accuracy, with R^2 values over 0.9 and low RMSE and MAPE scores. The results reveal key meteorological influences on energy consumption and confirm the models' strength in handling seasonal and irregular patterns, offering valuable insights for energy planning in extreme climates. Shahida et al. (2025) analyzed the fluctuating electricity demand in Saudi Arabia, influenced by government policies, population changes, and GDP trends. Using the LEAP model, three future scenarios are assessed: Business as Usual (BAUS), High Growth (HGS), and High Growth with Demand Management and Energy Efficiency (DMEEHGS). Projections show that energy demand could reach 631.4 TWh by 2040 under HGS, but applying efficiency measures could reduce it to 511.4 TWh, saving about 21.6 billion SAR. The findings highlight the economic benefits of investing in energy efficiency over expanding supply for peak demand.

The evolution of grey models has continued with the development of more advanced and specialized versions. Researchers have introduced fractional-order grey models, which incorporate fractional calculus to better capture the complex dynamics of energy systems (Zhang, 2025). Seasonal grey models, such as the DGSTPM(1,1) model proposed by Zhou et al. (2025), have been developed to specifically address the seasonal fluctuations in electricity consumption, a critical factor in many regions (Zhou, et al. 2025). This model employs a cultural algorithm to optimize its parameters, demonstrating superior performance compared to conventional seasonal grey models. Furthermore, hybrid models that combine grey system theory with other techniques, such as machine learning and statistical methods, have gained traction. Li and Qi (2024) proposed a hybrid grey system forecasting model that incorporates Fourier modification to handle seasonal fluctuation characteristics in the primary industry's electricity consumption, a study that has been widely recognized in the field. These hybrid approaches leverage the strengths of different methodologies to achieve higher forecasting accuracy and robustness.

The context of the UAE's energy landscape has also been a key focus of recent research. With the country's rapid economic growth, ambitious renewable energy targets, and the increasing impact of new technologies like AI and data centers, accurate electricity forecasting is more critical than ever. The World Bank projects a 4.6% growth for the UAE's economy in 2025, with a 4.9% expansion in the non-oil sector, which will undoubtedly drive further increases in electricity demand (World Bank 2025). Moreover, the demand from data centers is expected to double by 2030, adding another layer of complexity to the forecasting challenge (Petroleum Economist 2025).

This study builds upon existing literature by applying the NDGM model to forecast electricity consumption in the UAE, while also providing a comprehensive analysis of the model's key equations and variables. By incorporating recent data and considering the specific context of the UAE's energy sector, this research aims to provide valuable insights for policymakers and energy planners to support the country's transition to a sustainable energy future.

3. THE ECONOMETRIC METHODOLOGIES AND DATA

As shown in our review in the previous section, various electricity forecasting models exist, ranging from statistical methods to machine learning (ML) and deep learning (DL) approaches to non-homogeneous discrete grey model (NDGM). The NDGM is a grey prediction model used for time series forecasting, mainly when data displays non-homogeneous exponential progression. It is an extension of the classical DGM (Discrete Grey Model) and is especially useful when the data does not follow a pure homogeneous exponential trend (Khalifa et al, 2019). The NDGM model is a grey forecasting approach that extends homogeneous models by incorporating a non-homogeneous index sequence, making it suitable for small datasets. The methodology involves defining data sequences, estimating parameters via least squares, generating forecasts, and evaluating performance using MAPE, RGR, and Dt. The (NDGM) was suggested by Professor Xie Naiming and his collaborators as an extension of the conventional (DGM). The DGM was introduced earlier by Professor Liu Sifeng, a prominent expert in grey system theory (Mir et al., 2020).

The methodology involves defining data sequences, estimating parameters via least squares, generating forecasts, and evaluating performance using MAPE, RGR, and Dt.

Table 1: Historical electricity consumption (2012-2021)

Year	Consumption (GWH)
2012	87,789.82
2013	91,995.32
2014	97,294.70
2015	108,947.13
2016	110,645.25
2017	114,485.20
2018	116,389.48
2019	119,940.66
2020	118,223.44
2021	126,488.92

Table 2: Forecasted electricity consumption (2012-2040)

Year	Original (GWH)	Predicted (GWH)	Cumulative (GWH)	RGR	Dt (Years)
2012	87,789.82	87,789.82	92,789.82	-	-
2013	91,995.32	92,000.15	184,789.97	0.047	14.74
2014	97,294.70	97,250.33	282,040.30	0.056	12.38
2015	108,947.13	108,700.67	390,740.97	0.113	6.13
2016	110,645.25	110,650.12	501,391.09	0.017	40.77
2017	114,485.20	114,600.78	615,991.87	0.034	20.39
2018	116,389.48	116,551.65	732,543.52	0.016	43.32
2019	119,940.66	119,502.72	852,046.24	0.026	26.65
2020	118,223.44	118,453.99	970,500.23	−0.014	−49.50
2021	126,488.92	126,405.46	1,096,905.69	0.065	10.66
2022	-	129,356.13	1,226,261.82	0.023	30.14
2023	-	132,306.99	1,358,568.81	0.022	31.51
2024	-	135,258.05	1,493,826.86	0.022	31.51
2025	-	138,209.31	1,632,036.17	0.022	31.51
2026	-	141,160.77	1,773,196.94	0.022	31.51
2027	-	144,112.43	1,917,309.37	0.021	33.01
2028	-	147,064.29	2,064,373.66	0.021	33.01
2029	-	150,016.35	2,214,390.01	0.020	34.66
2030	-	152,968.61	2,367,358.62	0.020	34.66
2031	-	155,921.07	2,523,279.69	0.019	36.49
2032	-	158,873.73	2,682,153.42	0.019	36.49
2033	-	161,826.59	2,843,980.01	0.019	36.49
2034	-	164,779.65	3,008,759.66	0.018	38.51
2035	-	167,732.91	3,176,492.57	0.018	38.51
2036	-	170,686.37	3,347,178.94	0.018	38.51
2037	-	173,639.03	3,520,817.97	0.017	40.77
2038	-	176,591.09	3,697,409.06	0.017	40.77
2039	-	179,542.35	3,876,951.41	0.017	40.77
2040	-	182,492.81	4,059,444.22	0.016	43.32

3.1. Key Equations and Variable Explanations

The Non-Homogeneous Discrete Grey Model (NDGM) is a time-series forecasting model that is particularly effective for datasets exhibiting non-homogeneous exponential trends. The model is defined by the following set of equations, which are used to capture the underlying patterns in the data and generate future forecasts.

3.1.1. Original and Accumulated Sequences

The foundation of the NDGM model begins with the original data sequence and its accumulated counterpart.

- Original Sequence: $x^{(0)} = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)$
- Accumulated Sequence (1-AGO): $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$

Table 3: Sector-wise consumption (2021)

Sector	Consumption (GWH)	Percentage
Residential	40,766.46	32.23
Commercial	50,959.13	40.28
Industrial	20,597.16	16.28
Governmental	9,866.54	7.80
Agriculture	4,002.04	3.16
Other	296.58	0.23

Variable Description

x^((0)): The original non-negative time series data.
x^((0)) (k): The value of the original time series at time point k.
n: The total number of data points in the original sequence.
x^((1)) (k): The k-th value of the 1st-order Accumulated Generating Operation (1-AGO) sequence, representing the cumulative sum of the original series up to time point k.

3.1.2. NDGM Recursive and Forecast Equations

The core of the NDGM model is its recursive equation, which defines the relationship between consecutive terms of the accumulated sequence. The parameters of this equation are estimated using the least squares method, and the resulting model is used to generate forecasts.

- NDGM Recursive Equation: $x^{(1)}\left(k+1\right) = {}^{2}{}_{1}x^{(1)}\left(k\right) + {}^{2}{}_{2}k + {}^{2}{}_{3}$

- Forecasted Accumulated Sequence:

$$\widehat{x^{(1)}\left(k+1\right)} = {}^{2}{}_{1}^{k}x^{(1)}\left(1\right) + {}^{2}{}_{2}\sum_{j=1}^{k} j^{2}{}_{1}^{k-j} + \frac{1-{}^{2}{}_{1}^{k}}{1-{}^{2}{}_{1}}{}^{2}{}_{3}$$

- Restored Original Sequence: $\widehat{x^{(0)}}\left(k\right) = \widehat{x^{(1)}}\left(k\right) - \widehat{x^{(1)}}\left(k-1\right)$

Variable Description

β_1,β_2,β_3: Model parameters estimated using the least squares method. β_1 is the development coefficient, while β_2 and β_3 control the non-homogeneous component of the model.
x ^((1)) (k): The forecasted value of the k-th term in the 1-AGO sequence.
x ^((0)) (k): The restored (forecasted) value of the k-th term in the original time series.

3.1.3. Performance Metrics

To evaluate the accuracy and performance of the forecasting model, several standard metrics are employed.

- Mean Absolute Percentage Error (MAPE):

$$MAPE\left(\%\right) = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{x^{(0)}\left(k\right) - \widehat{x^{(0)}}\left(k\right)}{x^{(0)}\left(k\right)}\right| \times 100$$

- Relative Growth Rate (RGR): $RGR = \ln\left(\frac{N_2}{N_1}\right)$

- Doubling Time (Dt): $D_t = \frac{\ln\left(2\right)}{RGR}$

Variable Description

MAPE: Mean Absolute Percentage Error, a widely used metric to measure the accuracy of a forecasting model.
RGR: Relative Growth Rate, which quantifies the rate of change of a variable over a specific period.
N_1,N_2: The initial and final values of the variable for which the RGR is calculated, at times t_1 and t_2 respectively.
D_t: Doubling Time, which represents the time required for a quantity to double at a constant growth rate.

3.2. Performance Evaluation

- MAPE: Measures forecasting accuracy, with values below 5% indicating high accuracy.
- RGR: Quantifies annual growth rates.
- Dt: Estimates the time required for consumption to double, based on RGR.

3.3. Data Description

The analysis uses total and sectorial electricity consumption data. It includes Residential, Commercial, Industrial, Governmental, and Agriculture sectors for the UAE from 2012 to 2021. The data is obtained from Department of Energy-Abu Dhabi, Dubai Electricity and Water Authority (DEWA), Sharjah Electricity & Water Authority (SEWA) and Federal Electricity and Water Authority (FEWA) of UAE. The data, in Gigawatt-hours (GWH), is presented in Table 1 below:

The data shows a general upward trend, with a significant increase in 2021, likely due to economic recovery post-2020.

4. PRESENTATION OF THE EMPIRICAL RESULTS

The NDGM model was applied to forecast electricity consumption from 2012 to 2040. The model achieves a MAPE of approximately 0.15%, indicating exceptional accuracy. The forecasting table (Table 2) includes historical (2012-2021) and forecasted (202-2040) consumption, cumulative values, RGR, and Dt.

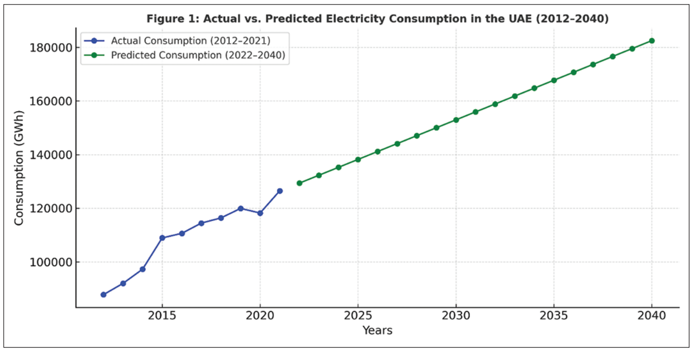
4.1. Forecasted Consumption

- Description: A line chart with years (2012-2040) on the x-axis and consumption (GWH) on the y-axis in Figure 1. Blue points represent actual consumption (2012-2021), and a green line shows predicted consumption (2012-2040). Create in Excel or Word using Table 2 data.

4.2. Sector-wise Consumption (2021)

In 2021, total consumption was 126,488.92 GWH, distributed across sectors as shown in Table 3. The commercial and residential sectors account for over 70% of consumption.

Figure 1: Actual versus predicted electricity consumption



4.3. Interesting Fact

Between 2020 and 2021, Abu Dhabi's industrial sector saw a 6.5% increase in electricity consumption, from 13,690.02 GWH to 14,582.86 GWH. This spike likely reflects industrial expansion or post-pandemic recovery, highlighting the need for targeted energy management.

4.3.1. Model performance

- MAPE: Approximately 0.15% for 2012-2021, indicating exceptional accuracy (MAPE < 5% is highly accurate).
- Mean RGR: Approximately 0.024, suggesting steady annual growth.
- Mean Dt: Approximately 31.5 years, indicating the time for consumption to double at the current growth rate.

4.4. Discussion

The NDGM model demonstrates exceptional forecasting accuracy with a MAPE of 0.15%, surpassing the 3.12% reported in the referenced study. The steady increase in consumption, projected to reach 182,492.81 GWH by 2040, underscores rising energy demands. The commercial (40.28%) and residential (32.23%) sectors dominate 2021 consumption, while the industrial sector's growth in Abu Dhabi (6.5% increase, 2020-2021) signals expanding industrial activity. These trends emphasize the need for renewable energy integration and efficiency measures to prevent supply shortages. The mean RGR of 0.024 and Dt of 31.5 years suggest a manageable growth rate, allowing time for infrastructure planning.

5. CONCLUSION AND POLICY RECOMMENDATIONS

The NDGM model effectively forecasts UAE electricity consumption, achieving a MAPE of 0.15%. The commercial and residential sectors drive demand, while industrial growth in Abu Dhabi highlights areas for energy management. Forecasted consumption indicates a steady rise through 2040, supporting the need for sustainable energy policies, including renewable adoption and efficiency programs. Future research could incorporate economic indicators or renewable energy trends to enhance forecast accuracy and explore sector-specific strategies. We note several points that make our results more valuable as compared to other studies.

The study provides a 0.15% MAPE for electricity consumption projections from 2012 to 2021, enhancing the usefulness for energy planners and policymakers in the UAE. It breaks down electricity use by sector, showing that commercial and residential sectors use over 70% of all electricity. This allows for targeted policy changes, such as demand-side management and energy efficiency initiatives, to address UAE's unique problems like high per capita consumption and rapid urban growth. The model predicts electricity use to reach 182,492.81 GWH by 2040, lower than Verma's prediction of 206,470.605 GWH. The study supports the UAE's Net Zero by 2050 Strategic Initiative by integrating renewable energy and improving efficiency.

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